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Lean Sensing: Exploiting Contextual Information for Most Energy-Efficient Sensing

Borja Martínez, *Member, IEEE*, Xavier Vilajosana, *Senior Member, IEEE*, Ignasi Vilajosana, and Mischa Dohler, *Fellow, IEEE*

Abstract— Event-driven applications are used to monitor the occurrence of certain events. In general, events are inherently stochastic, and the main function of the system is precisely to detect and report the occurrence of such events. Those cyber-physical technologies are being widely deployed in cities around the world and one of their critical aspects is energy consumption, as they are mostly battery powered. One of the most representative examples of such applications is Smart Parking. Since parking sensors are devoted to detect parking events in almost-real time, strategies like data aggregation are not well suited to optimize energy consumption. Furthermore, data compression is pointless, as events are essentially binary entities.

Therefore, this article introduces the concept of *Lean Sensing*, which enables the relaxation of sensing accuracy at the benefit of improved operational costs. To this end, the article departs from the concept of randomness and it explores the correlation structure that emerges from it in complex systems. Then, it examines the use of this system-wide, aggregated, contextual information to optimize power consumption, thus going in the opposite way: from the system-level representation to individual device power consumption. The discussed techniques include customizing the data acquisition to temporal correlations (i.e., to adapt sensor behavior to the expected activity) and inferring the system-state from incomplete information based on spatial correlations. These techniques are applied to real-world smart parking application deployments, aiming to evaluate the impact that a number of system-level optimization strategies have on devices power consumption.

I. INTRODUCTION

MOST of us suffer the experience of driving into town looking for some spot to park. This is a very familiar problem that citizens around the world face every day. As a result, citizens have developed some (sometimes rather efficient) strategies to deal with it. These strategies are usually based on prior experience turned into intuitions to deal with the complexity of urban living.

In theory, the state of an individual parking bay can be considered a stochastic process [1]; thus, the occupancy of a specific spot is intrinsically unpredictable. However, we intuitively understand that parking availability depends strongly on the quantity and diversity of spaces, time of the day, number of drivers in the vicinity, specific area regulations and many other undetermined variables which yield to specific characteristic

behaviors. For instance, on a city-level scale and using a downtown area as an example, parking demand tends to increase early in the day, holds at a relatively high level throughout the mid-day, and then spikes in the evenings when drivers pursue leisure activities (restaurants, cinemas, theaters, etc.).

There have been many studies in the past to analyze the structure of the parking availability in cities [2]. Whilst data has traditionally been collected manually, the usage of automated instrumentation through on-street parking sensors has become popular in different cities around the world, with the aim to improve the efficiency of the operation and management of public parking [3]. Representative examples are San Francisco, Los Angeles, Moscow, Nice, London and Barcelona, among many others. In there, small sensing devices have been deployed in every parking spot within large monitored urban areas. The benefits of these devices are undeniable; they have proven to be very useful in helping cities to better understand parking patterns, and they have become a very valuable tool in optimizing parking operations as well [4]. Moreover, they are enabling new services to the citizens as help drivers to find parking spaces more efficiently, reduce the hustle and bustle of traffic [5], and on-street parking reservation [6], [7], among others, thus providing an improved urban user experience.

However, in many cities, there is a common concern about the cost-benefit trade-off of this solution. The deployment of thousands of sensors in each parking bay involves a large upfront investment by public administrations or parking operators, and it imposes additional complexity on the operational side. As a result, some previous studies have analyzed the cost-benefit relationship of such a solution [8]. Some other studies take a more conceptual approach and have built a model to reduce deployment costs by providing sensor readings on only a fraction of the parking spots in a given area [9], followed by the use of extrapolation to calculate city-wide saturation levels [10].

Nevertheless, none of them have centered their efforts to the trade-off between the total cost of the device (including the cost of sensor itself, mostly determined by the battery size, but also the maintenance cost) and the application detection accuracy (how precise is the representation of the system provided by the application), given a service level agreement (SLA) established between city/operator and smart parking solution provider.

In a classical approach, applications parameters (e.g., sampling rate, network throughput, etc.) determine the energy consumption of the device which in turn limits its lifetime. In our study we propose an inverse approach, fixing the agreed

B. Martínez is with Universitat Autònoma de Barcelona (UAB), Spain and Worldsensing, Barcelona, Spain. (e-mail: borja.martinez@uab.cat)

X. Vilajosana is with Universitat Oberta de Catalunya (UOC), Spain and Worldsensing, Barcelona, Spain.

I. Vilajosana is Worldsensing, Barcelona, Spain.

M. Dohler is with King's College London and Worldsensing, London, UK.

lifetime of the device and determining the configuration parameters accordingly so the lifetime is met. What we evaluate then is not the expected lifetime but the impact in the reconstruction of the information due to a more relaxed capabilities of the device. Even more, we explore a set of system-level optimization strategies to impact on energy consumption. This approach deals with the balance between sensing accuracy and energy usage and we show how energy can be optimized by adapting sensing to application behavioural patterns. This proposal has been validated with real-world datasets from two different cities, each having several hundred of sensors deployed.

The article is organized as follows. Section 2 examines the datasets from a system-level point of view, in order to extract and visualize behavioral patterns. Contextual information is analyzed to better understand the application itself, with the confidence that this system-wide perspective can be used to optimize the energy efficiency of the system. Additionally, system-level metrics are defined. Section 3 provides a description of existing commercial off-the-shelf technologies and formalizes the device energy consumption model. Finally, in Section 4, the article proposes and validates an adaptive sensing approach which customizes the sensing performance according to the specific spot activity, but targeting an overall system optimization. Section 5 concludes the article.

II. DATA STRUCTURE

Enormous efforts have been made to reduce the energy (and bandwidth) consumption of devices [11] by compressing the information to be transmitted [12] [13], aggregating data [14], or even by not distributing the information at all but making the right decisions that are locally based on the information available [15]. However, in event-driven applications, there is no reasonable alternative to transmitting every single event. In addition, events are often expressed as boolean variables and rendering realtime compression techniques useless.

Consider the example of parking sensors. When a car is detected, the sensor communicates the event to the data-collection center so that system managers can keep track of the state. The parking event must be reported (as opposed to be aggregated to save energy), as the main function of these devices is precisely to monitor the occurrence of these events in (almost) realtime. Besides, a minimum amount of information is encapsulated at each message, which is usually incompressible considering that the state can be codified using a single bit. Even more, we cannot consider the parking application to be an alarm-based system as those addressed in [15], because all events are reported and not only those that have a special meaning or relevance.

Under these circumstances, it seems difficult to find alternatives to save energy other than using more efficient technologies. However, little attention has been paid to the application itself and to how the monitoring service is provided [16]. This not only holds true for smart parking but a wide range of industrial and civil applications [17].

Modern distributed monitoring systems are typically made up of two main layers [18]. The hardware infrastructure is

composed of thousands of networked embedded devices, the operation of which (although interconnected) is in essence independent. Above this hardware layer, software and service technologies enable high-level access and utilization of the real-world data and resources, which is usually inferred or extracted by advanced analytics [19]. This is the layer we pay attention to in this work.

Specifically, in this article, we introduce a concept referred to as *Lean Sensing* which aims to improve the cost-benefit of the application from a system wide perspective, taking into account the predictable behavior of the agents involved in the target application and, thus, being able to relax sensing requirements due to its prediction capability. The system described here is designed to identify and visualize patterns in a complex, macro-scale monitored process, and it is assumed that the provided monitoring service drives the optimization policies. Notably, as the next section shows, it is also in these patterns where one can identify some key aspects to support the design of efficient energy management strategies. This approach is similar to what has been successfully applied to other contexts, e.g., load anticipation in smart grids [20] [21]. In the following sections, we present some of the information that is obtained by a parking management tool, which will be used further to determine behavioral patterns and will be the basis for the proposed optimization framework.

A. System state: Occupancy

The system occupancy is not related to the specific state of a particular parking spot, but to the percentage of time a spot is occupied over a period of time. For traffic management, the historical average occupancy of the spot provides more information than the current state at a specific time. Likewise, the mean occupancy of an area provides more information than the state of a single sensor. Occupancy is the most intuitive and useful indicator for this particular application.

More formally, the following definitions will be considered in the remainder of this article:

1) *Sensor Occupancy*: S is the time ratio a specific spot has been occupied during a given time-slot. It is defined as a multi-dimensional variable, $S_{i,j}^{(k)} \in [0, 1]$; where index $i=1\dots N_H$ accounts for the time-slot during the day (typically the time-slot is one hour); $j=1\dots N_D$ denotes the day of the monitored period; and finally, index k refers to the specific sensor.

2) *System Occupancy*: the system occupancy state is obtained by averaging the considered set of related sensors at each time slot, N_S being the total number of sensors that are aggregated. This concept can be applied to the whole system, to a sector or to any subset of related sensors.

$$S_{i,j} = \frac{1}{N_S} \sum_{k=1}^{N_S} S_{i,j}^{(k)} \quad (1)$$

3) *Occupancy Reconstruction Error*: relates to the difference between the system occupancy state, which is built having a complete knowledge of the system, and the state inferred with partial information. Specifically, the reconstruction error is defined in Eq. (2), \hat{S} being the system occupancy state estimated from incomplete information.

$$\epsilon_S = \frac{1}{N_H \cdot N_D} \sum_{i=1}^{N_H} \sum_{j=1}^{N_D} |S_{i,j} - \hat{S}_{i,j}| \quad (2)$$

To illustrate these concepts, Fig. 1 shows the system occupancy state registered in a metropolitan area during one month (February). The colormap represents the average occupancy in a commercial sector of nearly 500 monitored spots. In this figure, \hat{S} is displayed hourly in the vertical direction and daily in the horizontal. To make the historical evolution more understandable, data is projected in two orthogonal directions. First, below the scale map, hourly occupancy has been averaged over each day in the figure. Then, this plot represents the daily mean evolution of the full period. Additionally, maximum and minimum daily occupancy have been represented. The second one, on the right-hand side of the scale map, is a projection of the hourly occupancy of every single month in the period. This figure captures with a single snapshot the historical hourly behavior, showing the variability of daily patterns during the period being studied.

This view can help to understand several patterns of citizen behavior: i.e., occupancy is much higher during daytime hours and is almost zero at night (note that these sensors are deployed in a commercial area); weekend specific patterns are noticeable, and they are appreciably different from the rest of the week days; finally, lower occupancy was registered in the first week of the period, most likely due to adverse weather conditions. These are some examples of useful information required for intelligent traffic management systems.

B. System activity and turn-over:

The activity (i.e., the number of events that happened in a given slot of time) and the number of turn-overs (which is directly related to the former) are essential indicators for mobility agents. Intuitively, activity provides an estimate of the flux of traffic that can be absorbed. For instance, in parking guidance systems, drivers can be redirected to areas whose activity is expected to be higher. Even more, activity can be used for adjusting prices and bounding minimum and maximum parking-times in paid parking areas.

Due to its relevance, activity should be well defined and precisely quantified. In this regard, this article formally complies with the following definitions:

1) *Sensor Activity*: the sensor activity R is the number of events occurring in one spot during a specific time-slot. $R_{i,j}^{(k)}$ is defined in a similar way as the occupancy. The index $i=1 \dots N_H$ designates the time-slot, $j=1 \dots N_D$ indicates the day, and k is the sensor index.

2) *System Activity*: the average activity of a set of sensors in each time-slot:

$$R_{i,j} = \frac{1}{N_S} \sum_{k=1}^{N_S} R_{i,j}^{(k)} \quad (3)$$

3) *Activity Reconstruction Error*: the error made while estimating the system activity with incomplete information \hat{R} .

$$\epsilon_R = \frac{1}{N_H \cdot N_D} \sum_{i=1}^{N_H} \sum_{j=1}^{N_D} |R_{i,j} - \hat{R}_{i,j}| \quad (4)$$

Fig. 2 shows the activity recorded in the commercial area of a small town. The displayed subset belongs to the first 28 days of December. The daily pattern indicates higher activity during the morning and afternoon, while it is very low at night. In addition, week and weekend days can be clearly differentiated. The historical data shows that, in general, activity increases throughout the week as the weekend approaches. Besides, special behavior is observed on holidays (around Dec. 25th).

In this application (for which all events detected are directly reported), the activity is not only related to physical detection, but to the number of radio messages generated. Thus, besides the fact that activity is an important system performance indicator, it has a direct impact on energy consumption as demonstrated in the next section.

C. Temporal Stability

In light of the above figures, the question then arises as to how the knowledge of this data patterns could be used in some efficient way. Section IV exploits some possible applications. However, before doing so, it is necessary to address the issue of repeatability. Repeatability is two-fold. On the one hand, it is essential for predictive management, as it enables making decisions based on past behavior. On the other hand, it provides the key to optimization policies: any engineering decision devised on the basis of patterns observed in past data should still be valid when projected onto the future.

Fig. 3 can help to clear up doubts about this fundamental question. This figure shows sensor activity averaged over a long period, with the particularity that sensors have been sorted by their activity. This arrangement reveals three different regions corresponding to sensors with low, medium and high activity. The behavior of three successive months has been superimposed (depicted by three different tones of gray). The replicated trend demonstrates an intuitive fact: when a spot has been very active in the past, it remains being active. Spot activity is highly dependent on the city environment (commercial parking, ATM, passing area, etc.). However, in this sense, the environment is basically static. Thus, the activity of each spot is expected to be stationary.

This important result ensures the stability of activity as a classification criteria, and thus guarantees that any design workaround that is tailored to a specific class of spots will be valid for the future, provided that the classification criteria is based on activity.

Fig. 3 reveals another suggestive pattern. Subplots 3a and 3b are recorded in two very different environments (a metropolis and a small town). Notably, the distribution shape is almost identical. This result suggests that there are some fundamental patterns underlying the system, independently of the city, and that developed policies may be valid for (quite) different deployments.

III. THE ROLE OF TECHNOLOGY

This section shifts momentarily our focus to the technology being used in smart parking deployments. As the goal of our study is to optimize the energy consumption of such devices using contextual information, we need an accurate knowledge

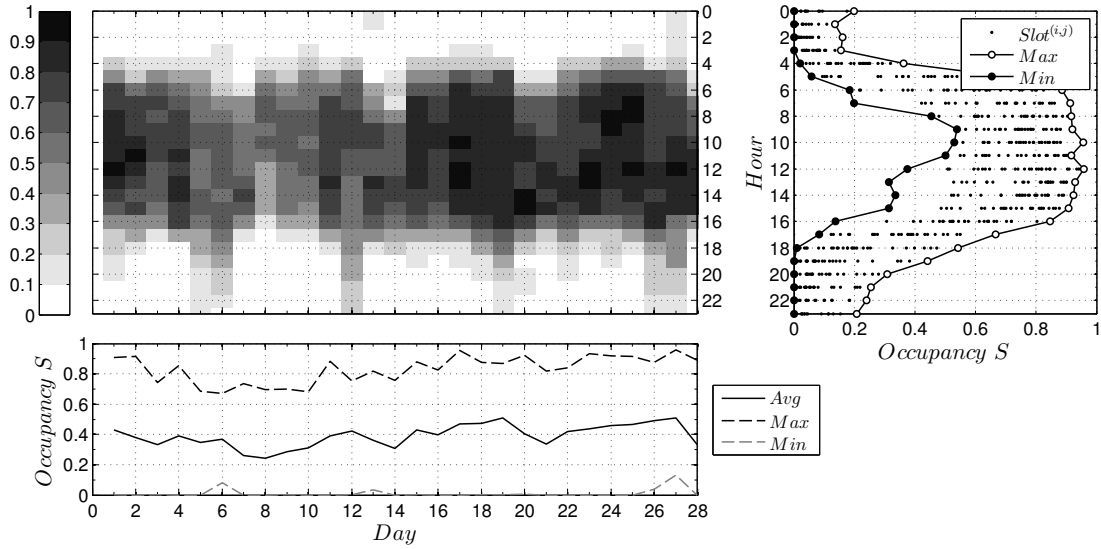


Fig. 1. System occupancy evolution in a metropolitan sector, from different perspectives. The chart displays 4 weeks, with a time-slot grid of 1 hour.

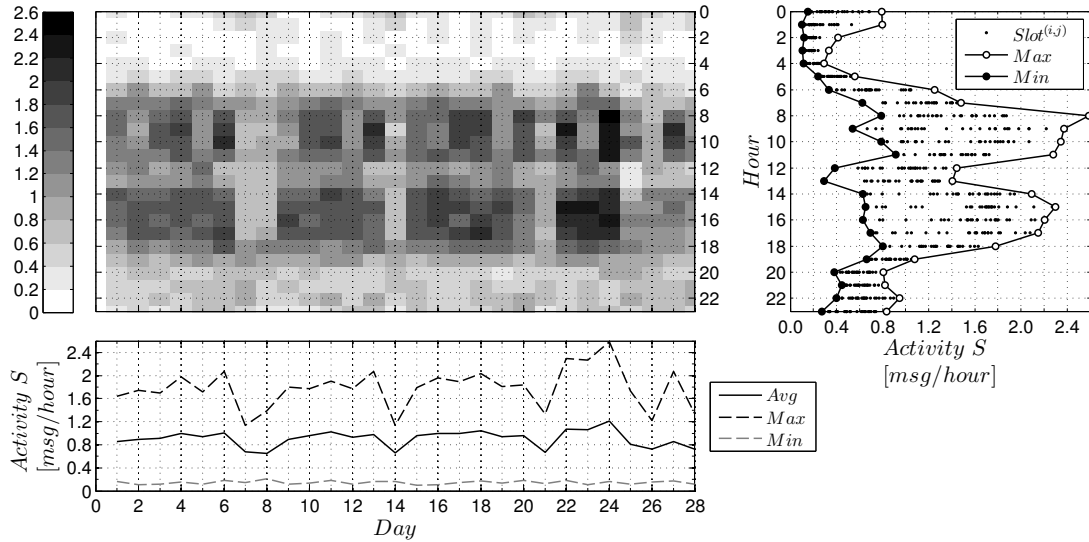


Fig. 2. System activity evolution in a small city, from different views. The chart displays 4 weeks, with a time-slot grid of 1 hour.

of how these nodes behave and where the energy is spent from an individual point of view. For this purpose, in this article we make use of the previously defined model to estimate the energy consumption of these devices. An extensive description of the derived model can be found in [22].

A. Energy Model Description

In general, embedded systems run a set of repetitive tasks. In most of the wireless sensors devices, sampling is performed periodically and some information is reported to the data collector center throughout the course of operation.

In terms of energy consumption, the application can be modelled mainly by these two contributions: periodic sampling and the reporting of physical events. These tasks are parametrized as follows:

- A *record* of N_S samples is acquired with a fixed interval time, T_{RCD} . The sensor comes to a decision about the occupancy state by analyzing the full record of samples.
- Events occur with a certain probability, generating radio messages spaced at characteristic time, T_{MSG} .

When sensors generate endogenous traffic according to some stochastic process distribution, the time elapsed between consecutive messages, T_{MSG} , should be characterized by an appropriate statistical estimator (often a simple average is enough). This approximation is reasonably good for long-term averaging.

1) *Sampling Characterization*: For each record composed of N_S samples, the total time the sensor remains switched on is given by $T_S \cdot N_S$, where T_S is the physical sampling interval (see Fig. 4) and use to be fixed by filter requirements.

The current of the acquisition block can be obtained by

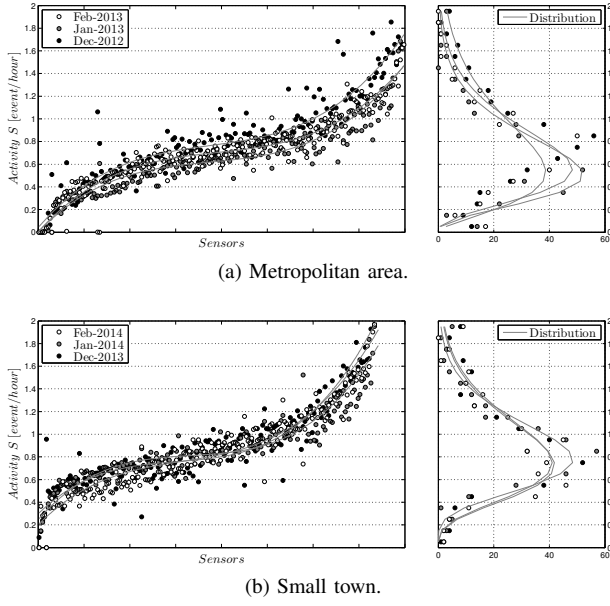


Fig. 3. Time evolution of the activity, with individual sensors sorted by activity and their histogram.

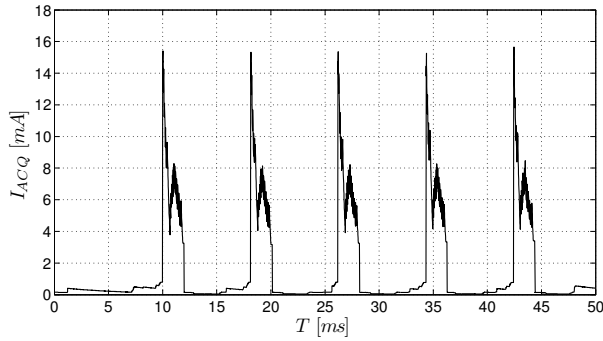


Fig. 4. Record composed of $N_S=5$ samples elapsed $T_S=8$ ms.

averaging the charge to get the N_S samples of the record over the time elapsed between consecutive records T_{RCD} , i.e. the wake-up period. In Eq. (5) \bar{Q}_{SNR} is the average charge to get one sample (area below the peaks curve in Fig. 4) and comprise both the sensor and the ADC conversion. $\bar{I}_{SNR}^{(STB)}$ accounts for the stand-by or quiescent current of the sensor.

$$\bar{I}_{ACQ} \cong \frac{\bar{Q}_{SNR} \cdot N_S}{T_{RCD}} + \bar{I}_{SNR}^{(STB)} \quad (5)$$

2) *Point to Point Communications*: The average power of the communications block can be expressed in terms of the charge required to send a radio message, \bar{Q}_{MSG} , and a characteristic time between consecutive events, T_{MSG} . The reported information is aggregated into a unique message. We assume that this message can be retransmitted a certain number of times, N_{RTX} , to increase the probability of success (Fig. 5).

$$\bar{I}_{NET} \approx \frac{N_{RTX} \cdot \bar{Q}_{MSG}}{\bar{E}[T_{MSG}]} = \frac{N_{RTX} \cdot \bar{Q}_{MSG}}{\hat{T}_{MSG}} \quad (6)$$

It is important to recall that our work is focused in Low Power Wide Area Network (LPWAN) technologies which are driving large scale deployments in smart city and smart metering applications. Those technologies rely on very robust modulations and low data rates thus enabling one-hop long range links [23], [24], [25], for which Eq. (6) is applicable. Multihop networks are not considered as industrial deployments on the field are clearly betting for LPWAN technologies.

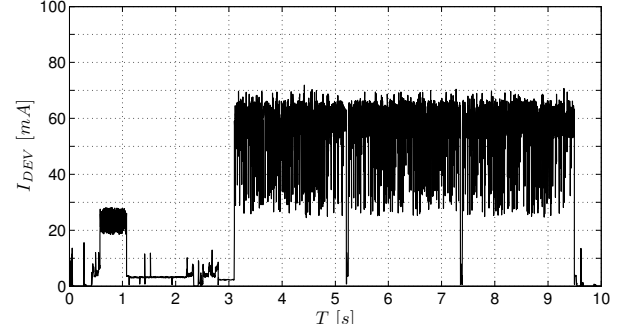


Fig. 5. Radio message: initialization and 3 retransmissions.

3) *Joint Model*: Eq. (7) combines the two main contributions of this application: sensing and communications, explicitly keeping technological and application parameters as independent variables. Recalling the meaning of each individual contribution, α can be interpreted as the charge per sample \bar{Q}_S and γ is an estimator of the average charge per message \bar{Q}_{MSG} . Regarding δ , it basically accounts for OS management consumption and quiescent DC/DC currents. Finally, it should be noted that, as this is essentially a bare reporting application, the cost associated with processing can be considered negligible. This is due to the low processing load, in addition to the several orders of magnitude difference between computing and transmitting assumed for current low-power wireless devices [11].

$$\bar{I}_{DEV} = \frac{\alpha N_S}{T_{RCD}} + \frac{\gamma N_{RTX}}{\hat{T}_{MSG}} + \delta \quad (7)$$

B. Operational Cost and Energy Constraints

There is one important aspect related to the operation and maintenance of systems like the smart parking application. In there, thousands of battery operated devices are deployed in a wide area requiring a periodic maintenance and battery replacement. The later is impacted by the energy saving policies, which tend to be the same for the overall system in traditional approaches, despite of having zones that suffer from higher levels of activity. Thus, some devices deplete their power more quickly than others, creating different usage patterns across the same network. We believe that it is very important to not only increase battery life by smart optimizations, but to also homogenize battery consumption across all devices in order to facilitate interventions and reduce maintenance costs by compacting maintenance operations [26].

Given the above reasons, this work considers the expected battery life to be a constraint (not a variable to be maximized),

and that the objective of the energy policy should be to ensure that the minimum expected life-time specification is met, while maximizing the system accuracy. With this aim, Eq. (7) can be interpreted as a parametric function binding together T_{RCD} and T_{MSG} . More specifically, when the expected battery life is fixed and the maximum average current I_{DEV} is thus constrained, and bearing in mind that α , γ and δ are constants that only depend to the technology, Eq. (7) defines one-to-one mapping of the expected activity and the recording interval (as the only free variables remaining are T_{RCD} and T_{MSG}). Then, we can estimate an upper bound for the recording interval isolating T_{RCD} as a function of T_{MSG} , once the expected activity of the sensor \hat{T}_{MSG} has been established:

$$T_{RCD}^{(MAX)} = f(\hat{T}_{MSG}) \quad (8)$$

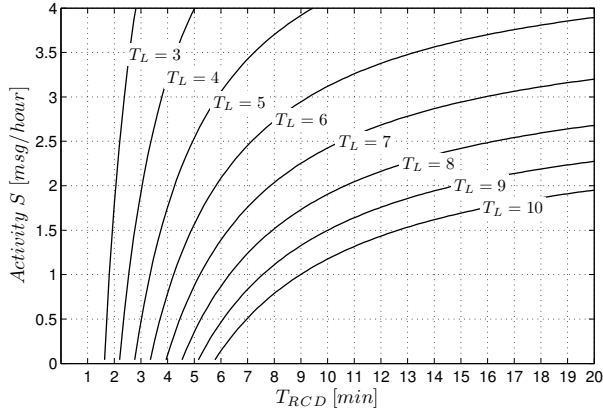


Fig. 6. $T_{MSG} \leftrightarrow T_{REC}$ mapping, as defined by Eq. (8), for different values of expected life-time T_L (expressed in years).

C. Experimental Setup

This study was developed on a proprietary custom platform for smart-parking applications. The main components were the Cortex-M4 32 bit processor, running with an RTOS systick interrupt of 1 ms, and a low-cost AGMR magnetometer characterized in Fig.4. This platform was equipped with a long-range radio module (See Fig.5)

For the described energy model, the following settings were used: the device requires $T_{SNS}^{(ON)} = 60s$ to determine the state of the spot, i.e. a record of $N_S = 7500$ samples acquired at $T_S = 8ms$; Lithium batteries had a total capacity of 30Ah, with a self-discharge ratio of 1%; finally, the radio module used a non-secure protocol with $N_X = 3$ (re)transmission attempts. Measured charge values for acquisition and radio are $\bar{Q}_{SNR} = 14.5 \pm 0.8 \mu C$ and $\bar{Q}_{MSG} = 136 \pm 6 mC$ [22].

Fig.6 shows a numerical simulation of Eq. (7), for the used platform and settings defined above. The black lines represent the mapping $f(\cdot)$ in Eq. (8), once I_{DEV} has been set so as to achieve the desired uninterrupted operation, T_L , for different target values measured in years.

IV. PERFORMANCE ANALYSIS OF ENERGY MANAGEMENT POLICIES

Once analyzed the particular characteristics of this application, i.e., how the monitoring service is provided, the intrinsic structure of parking patterns and the underlying technology, this section concludes with an analysis of several optimization strategies. These strategies are evaluated on the basis of the energy model described in Section III, with the main focus on quantifying their impact on the service provided under system-level metrics.

The dataset for this section have been provided by World-sensing. Data were gathered over three months from about 1000 outdoor devices, deployed in two different scenarios. Unless otherwise stated, the first month is used for development and training, whereas the last two months are used for validation. This is motivated by an operational fact:

The deployment of a smart parking application is usually executed in different phases. First an installation phase takes care of embedding the sensors in the ground and installing the network infrastructure, deploying the server applications and data analytics services. Once the infrastructure is deployed, a second stage is used to calibrate and test the system, before giving the control of the system to the end user (customer). The training of the system happens during this second phase that may last several weeks (typically one month).

A. Temporal Decimation: Fixed Recording Interval

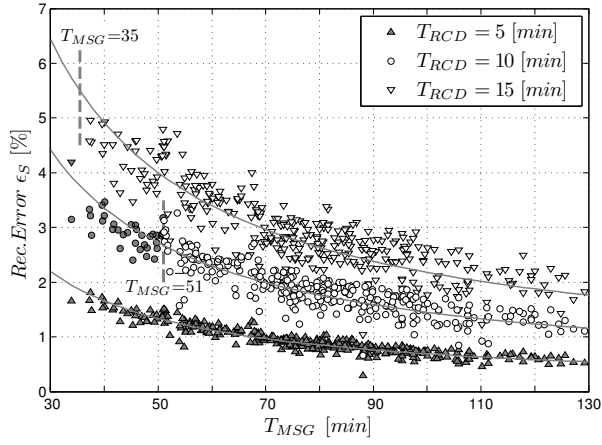
Classic sampling methods may not be the best choice for systems in which not all sensors experience the same activity. On the one hand, if a fast recording rate is selected, most of the sensors will deplete their batteries before the scheduled intervention time. On the other hand, if a slow rate is selected in order to ensure that all sensors meet the desired life-time specification, the information provided by the sensors may be too inaccurate. Therefore, the first issue to address is to quantify the system representation accuracy as a function of the sampling rate, i.e., how the time between records affects the accuracy of the system.

Fig. 7 shows the relation between the occupancy reconstruction error $\epsilon_S^{(k)}$ of each single sensor and the activity $S^{(k)}$ (measured as the average interval between events, \hat{T}_{MSG} , which is the inverse of the number of messages per time-slot). The figure aims to present a scenario where nodes target a 10 years lifetime. Note that the reconstruction error collects the deviations caused by the time difference between the instant when the event is detected and when the event actually happened.

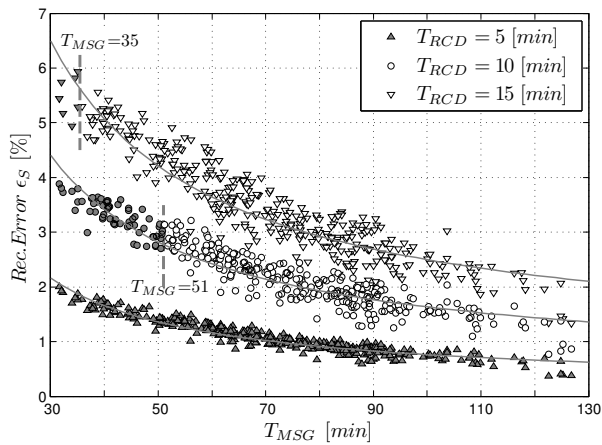
The figure shows three sets of points, each corresponding to a fixed interval time between sensor records of $T_{RCD} = \{5, 10, 15\}$ minutes, respectively. For each recording interval, Eq. (7) has been used to find the maximum number of messages for which the device is still within specifications (i.e., its battery survives the required amount of time).

The results can be summarized as follows:

- $T_{RCD} = 15mins$: Eq. (8) is satisfied for $T_{MSG} \approx 35min$. This means that if nodes wake up and sample a data record every 15 min in order to detect if there is an state



(a) Metropolitan area.



(b) Small town.

Fig. 7. Reconstruction accuracy vs. activity, for different recording intervals.

change and events occur every 35 min in average, the system lifetime will expand over 10 years. Obviously, this set (represented with inverted triangles) has the highest reconstruction error, between 2.5% and 5%, meaning a lesser accuracy in determining occupancy.

- $T_{RCD}=10\text{mins}$: The limit value given by Eq. (8) for this case is $T_{MSG} \approx 51\text{mins}$. While most of the sensors are still within specifications (white circles), some of them will probably deplete their batteries before the end of their expected life, which is fixed to 10 years (dark circles).
- $T_{RCD}=5\text{mins}$ (triangles): Operating with these settings, none of the sensors will fulfill their expected life, independently of T_{MSG} . As expected, this set has the lowest reconstruction error, as nodes sample more often.

Notably, the activity of the sensor clearly affects the reconstruction error of the occupancy (trends are represented with solid lines in the figure). This is something that is perhaps not obvious, but can be understood as follows: if a sensor is very active (because it is changing the state quite quickly) and the sampling rate is low, then the error introduced can be relatively high, as each change in the state can potentially induce some inaccuracy. In other words, the sampling rate is too slow in comparison to the time the sensor remains in the same state.

B. Temporal Decimation: Adaptive Recording Interval

The recording interval settings can be set from an alternative point of view. In this new approach, the sampling rate is no longer a system feature, but a control parameter for adjusting the power consumption of the system. Specifically, as the time between records increases, less power is consumed. Then, by increasing the record interval it is possible to balance the extra power consumption associated to higher activity. As stated in Section II-C, system activity can be considered constant for each specific sensor in a statistical sense. Then, the recording interval T_{RCD} can be adjusted for each sensor so that the expected life can be guaranteed, e.g., decreasing the sampling rate in active nodes and increasing it on those not so active.

Fig. 8 shows a scatter-plot representing the expected life for each sensor when using this adaptive approach. The $T_{RCD} \leftrightarrow T_{MSG}$ mapping, given by Eq. (8), is estimated after a one-month learning stage, but the sensors are displayed at their actual measured T_{MSG} over the full period. As it can be seen, by letting nodes sample at different intervals T_{RCD} according to their actual activity T_{MSG} , it is possible to adjust the overall system lifespan to the target specifications (the figure shows two examples of 7 and 10 years, respectively). The main benefit of this customized sampling is that it homogenizes the expected life of sensors by balancing the power consumption, and thus it minimizes premature battery death or non-scheduled interventions.

Obviously, some fluctuations exist due to the uncertainty assumed when using a learning stage. However, with the exception of a few devices, the vast majority of them can fulfill the expected life-time specification, at least according to everything that concerns the battery capacity.

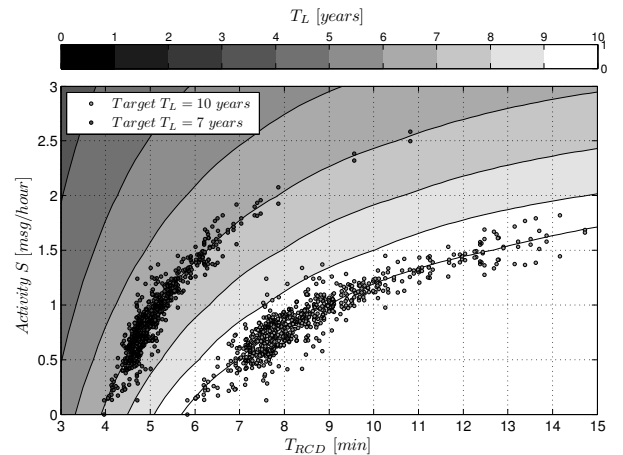


Fig. 8. Activity vs. adaptive record interval, for two different targets.

The reconstruction error of each sensor can be evaluated for different recording intervals, which in turn are determined by the activity of the sensor (when energy is bounded). Fig. 9 shows the reconstruction error for each individual sensor, $\epsilon_S^{(k)}$, displayed as a function of the record interval, comparing both approaches. The results show devices running with adaptive recording interval (triangles), superimposed to results expected for different values of fixed recording intervals. In this case,

the gray circles indicate the error averaged for all sensors for each specific recording interval. For each fixed value, the small black dots mark the value of each sensor, illustrating the variability in the system; and the black, solid line is the trend of the averaged errors.

Obviously, sensors with slower rates are expected to be less accurate, at least individually. Even more, when using adaptive sampling intervals that are above $T_{RCD} = 8\text{mins}$, the reconstruction error appears over the averaged trend of fixed settings (reflecting the fact that reconstruction error increases as the devices are more active, already observed in Fig. 7). A natural question arises as to how the error of these more active devices affects to the reconstruction error of the whole system, and whether the negative effect of this small set could be compensated with the better accuracy of less active devices that together form a larger set. This assumption is motivated by the asymmetric distribution of node activity as seen previously in Fig. 3.

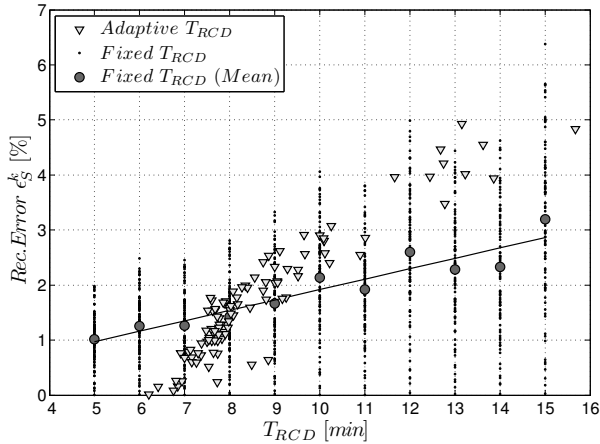


Fig. 9. Reconstruction Accuracy vs. Recording Interval (Sensor view).

To answer this question, Fig. 10 shows the system reconstruction error ϵ_R vs. the record interval T_{RCD} . As expected, the system error is much lower than the individual contributions, as errors are statistically compensated.

The gray circles show the error when using a fixed recording interval, and the dashed line indicates the trend when the (fixed) T_{RCD} is progressively longer. The black cross marks the reconstruction error of the adaptive sampling rate solution, placed at the averaged \hat{T}_{RCD} of all sensors in the adaptive configuration. Notably, the cross lies below the trend, which indicates that the better accuracy of most of the sensors in fact tend to compensate for the worse accuracy of the small set of most active devices.

Moreover, the size of the circles in Fig. 10 is proportional to the number of sensors running with a fixed sampling rate whose expected life is shorter than required by specifications (10 years in this example). While the reconstruction error of the adaptive approach is approximately equal to the fixed one configured at $T_{RCD} = 8\text{mins}$, with these settings, the latter causes 53% of the devices to have problems at the end of their service life, while the former drops below 1%.

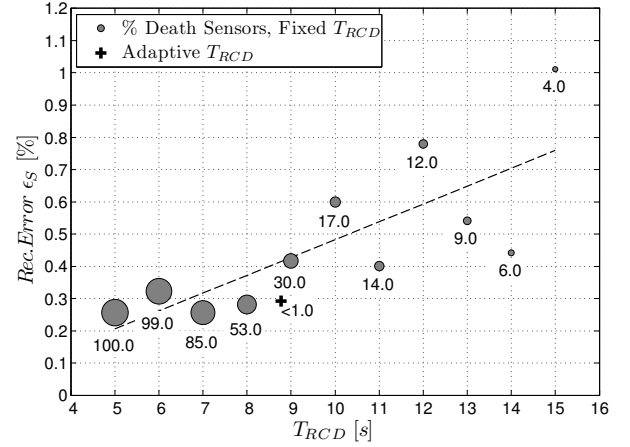


Fig. 10. Reconstruction Accuracy vs. Recording Interval (System). Ratio potentially problematic devices estimate due to premature death for $T_{RCD} = 10\text{mins}$.

C. Reconstruction under Failure: Spatial Correlations

Independently of the approach, there is a certain risk of device failure before a scheduled intervention. For instance, Fig. 10 shows the ratio of potentially problematic devices when using a fixed record interval. However, even when using a customized record interval, some deviations from the predicted behavior may possibly occur in the learning stage, which itself may result in a premature death. Obviously, in addition to the battery life, the problem of physical device failure, vandalism, etc. is always present. Therefore, this section aims to evaluate the accuracy of the system state reconstruction when the information is incomplete, whatever the reason for the failure is.

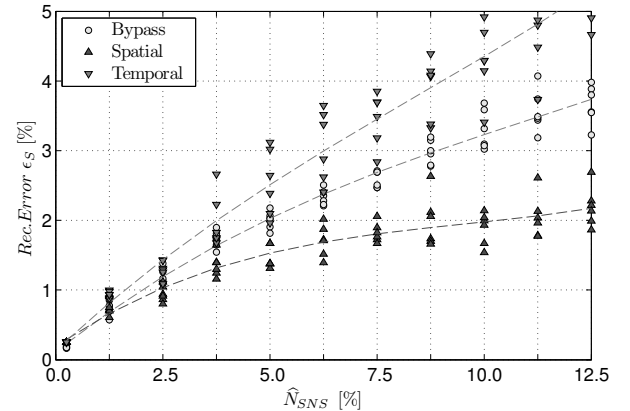


Fig. 11. Reconstruction error vs number of lost Sensors.

Fig. 11 shows the results of different strategies for rebuilding the system occupancy state when the data associated to a set of devices is not available. Reconstruction error is plotted against the ratio of unavailable sensors. In this figure, each dot represents a period of 14 days. There are six dots for each coordinate value, corresponding to six 14-day periods over the three months. This particular arrangement is intended to verify that the temporal behavior is stable.

The figure shows three different sets of points, depending on the strategy taken:

- **Bypass Method:** (Shown in light gray.) Unavailable devices are simply omitted, and the state is built statistically from the remaining sensors.
- **Temporal Self-Similarity Method:** (Shown in black.) Missing devices are modeled from their own past pattern, taking advantage of the sensor's self-similarity. The obtained model is used to build the system state. Best results were achieved when using the last known week pattern.
- **Spatial Similarity Method:** (Shown in dark gray.) Missing sensors are replaced by the physically closest operative neighbor, taking advantage of the spatial similarity.

As a concluding remark, in general there is a strong spatial correlation between sensors which makes the Spatial Similarity Method effective in most of the cases. Temporal correlations however decrement the accuracy of the system unless they are correlated to the overall system state and not to its own individual history. This is interpreted as a further demonstration of the random nature of individual parking spots. Finally, the introduced error due to inferring the state of some sensors is relatively small (lower than 4% considering a 10% of lost sensors) which tells us that an operative intervention to replace batteries would not be cost-effective unless the number of lost sensors is significantly large.

V. CONCLUSIONS

This article used the smart parking real-world application as a case study to introduce novel alternatives for efficient energy management of large wireless sensor networks.

The derived insights can be seen as tools for applications in which classical strategies such as data compression or local processing are not well suited. Our introduced approach is based on exploiting contextual information from a management system point of view, referred to as *lean sensing*. This approach stimulates the introduction of system-level metrics, which in turn allows to relax some requirements for individual sensors. Besides, the article, presents an adaptive sampling approach based on the analysis of historical data evolution. The developed lean sensing framework enables a global system improvement by constraining the operation of most active devices while relaxing those with lesser activity. The approach facilitates energy consumption balancing enabling all sensors to meet a desired lifetime regardless of their activity level. As discussed, this homogenization has a substantial impact on operational costs and thereby minimizes non-scheduled (costly) interventions.

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